Improved Dot Diffusion by Diffused Matrix and Class Matrix Co-Optimization

Jing-Ming Guo, Member, IEEE, and Yun-Fu Liu

Abstract—Dot diffusion is an efficient approach which utilizes concepts of block-wise and parallel-oriented processing to generate halftones. However, the block-wise nature of processing reduces image quality much more significantly as compared to error diffusion. In this work, four types of filters with various sizes are employed in co-optimization procedures with class matrices of size $8 \times 8$ and $16 \times 16$ to improve the image quality. The optimal diffused weighting and area are determined through simulations. Many well-known halftoning methods, some of which include direct binary search (DBS), error diffusion, ordered dithering, and prior dot diffusion methods, are also included for comparisons. Experimental results show that the proposed dot diffusion achieved quality close to some forms of error diffusion, and additionally, superior to the well-known Jarvis and Stucki error diffusion and Mese’s dot diffusion. Moreover, the inherent parallel processing advantage of dot diffusion is preserved, allowing us to reap higher executing efficiency than both DBS and error diffusion.

Index Terms—Digital halftoning, direct binary search, dot diffusion, error diffusion, ordered dithering.

I. INTRODUCTION

Digital halftoning [1], [2] is a technique for converting grayscale images into binary images. These binary images resemble the original images when viewed from a distance due to the low-pass filtering nature of the human visual system (HVS). The technique is used widely in computer printer-outs, printed books, newspapers and magazines, as they are mostly constrained to the black-and-white format (with and without ink). Another major application of digital halftoning is color quantization with a restricted color palette. Halftoning methods include ordered dithering [1], dot diffusion [3], [4], error diffusion [5]–[16], and direct binary search (DBS) [17]–[23]. Among these, dot diffusion offers good tradeoff between image quality and processing efficiency. Although some researchers propose an error-diffusion-based approach that encompasses the parallel processing property as that in dot diffusion, the resulting efficiency is still lower than that of dot diffusion. Detailed comparisons are provided at the end of Section IV.

Ordered diffusion is a parallel processing method, and is generally distinguished into clustered-dot and dispersed-dot halftone screens. The image quality produced by ordered dithering is inferior to that of DBS, error diffusion, and dot diffusion, since the error induced during the halftoning procedure is retained in each halftone pixel. In contrast, error diffusion avoids this, as the quantized error is designed to be compensated by neighboring pixels. This results in error-diffused halftones generally having the pleasant-looking blue noise property [24]. However, error diffusion lacks the advantage of parallel processing and, thus, its inferior processing efficiency to ordered dithering. The DBS is currently the most powerful halftoning method to generate halftones. However, its time-consuming iterative approach renders it difficult to be realized in commercial printing devices.

Dot diffusion reaps benefits from parallel processing through utilizing a diffused weighting and a class matrix. Prior studies on dot diffusion techniques focused on class matrix optimization (Knuth [3] and Mese [4]). However, the diffused weighting of these works are fixed without carrying out optimization procedures. This study considers three issues, namely diffused weighting, diffused area, and training sets, in order to improve image quality. The proposed method approximates error diffusion halftoning while maintaining parallel processing capability.

The rest of this paper is organized as follows. Section II introduces prior error diffusion and dot diffusion methods. Following which, Section III describes the proposed dot diffusion method. Finally, Section IV shows the experimental results and Section V draws the conclusions.

II. OVERVIEW OF ERROR DIFFUSION AND DOT DIFFUSION

This study presents an improved dot diffusion approach with approximate quality to traditional error diffusion. To facilitate the understanding of the differences between error diffusion and dot diffusion, an overview of error diffusion is provided in Section II-A. In Section II-B, dot diffusion methods proposed by Knuth and Mese will be briefly introduced, of which major weaknesses and differences will be highlighted.

A. Traditional Error Diffusion

Figs. 1(a) and 2 show the scanned path and processing flow chart of error diffusion, respectively. Here, we numerically define 255 as a white pixel and 0 as a black pixel. The variable $x_{i,j}$ denotes the current input pixel value, and $x'_{i,j}$ denotes the diffused error accumulated from neighboring processed pixels. The variable $b_{i,j}$ denotes the binary output, and the variable $l_{m,n}$ denotes the error kernel. The variable $v_{i,j}$ denotes the
modified gray output, and \( e_{i,j} \) denotes the difference between the modified gray output \( y_{i,j} \) and the binary output \( b_{i,j} \). The relationships of these variables are organized as follows:

\[
\begin{align*}
\psi_{i,j} &= x_{i,j} + \triangle x_{i,j}^t, \\
\triangle x_{i,j}^t &= \sum_{m,n \in R} c_{i+m,j+n} \times h_{m,n}
\end{align*}
\]  
(1)

\[
e_{i,j} = \psi_{i,j} - b_{i,j}, \quad \text{where} \quad b_{i,j} = \begin{cases} 0, & \text{if } \psi_{i,j} < 128 \\ 255, & \text{if } \psi_{i,j} \geq 128 \end{cases} \tag{2}
\]

B. Traditional Dot Diffusion

The main differences between dot diffusion and error diffusion are the processing order, diffused weighting, and the diffused direction. Suppose an original image of size \( P \times Q \) is divided into nonoverlapped blocks of size \( M \times N \), as shown in Fig. 1(b) (suppose \( M \times N = 8 \times 8 \)). A class matrix, which is of the same size as a divided block, is used to determine the processing order in a block. The flow chart of dot diffusion is the same as that in Fig. 2, while (1) is modified as follows:

\[
\psi_{i,j} = x_{i,j} + \triangle x_{i,j}^t, \quad \text{where} \quad \triangle x_{i,j}^t = \sum_{m,n \in R} c_{i+m,j+n} \times h_{m,n} \,
\]  
(3)

where the variable \( h_{m,n} \) denotes the diffused weighting (suppose support region \( R \) is of size \( 3 \times 3 \)) as arranged below

\[
\begin{bmatrix}
  h_{-1,-1} & h_{-1,0} & h_{-1,1} \\
  h_{0,-1} & C & h_{0,1} \\
  h_{1,-1} & h_{1,0} & h_{1,1}
\end{bmatrix}.
\]  
(4)

The variable \( C \) denotes the pixel currently being processed. Notably, the error can only diffuse to neighboring pixels that associates to the members in the class matrix with a higher value than its own associated value. These are pixels that have yet to be binarized. The variable \( \text{sum} = \sum_{m=n}^{1} h_{m,n} \) is the summation of the diffused weights corresponding to those unprocessed pixels. An example as shown in Fig. 1(b) demonstrates the concepts introduced above. The Knuth’s 8 \( \times 8 \) class matrix is used as an example. The values of \( \text{sum} \) associated to members with values 0 and 7 in the class matrix, are 12 and 7, respectively. The parallel processing property of dot diffusion can be appreciated from Fig. 1(b), where the pixels associated to the
same value in the class matrix can be processed concurrently. Hence, suppose the class matrix is of size $8 \times 8$, a dot-diffused image can be obtained in 64 time units.

The processing orders within the class matrix play a significant role in the quality of the reconstructed image. Knuth’s optimization approach attempts to reduce the number of barons (coefficients in the class matrix with no higher pixel value surrounding it) and near-barons (coefficients in class matrix with only one higher pixel value surrounding it). The concept is straightforward since a baron leads to a nondiffusible quantized error, and a near-baron only allows the quantized error to diffuse in one way. However, the Knuth’s method does not consider the nature of the human visual system (HVS) in their optimization procedure. To resolve this problem, the optimiza-
III. IMPROVED DOT DIFFUSION USING OPTIMIZED DIFFUSED WEIGHTING AND CLASS MATRIX

As mentioned, two dot diffusion parameters, the diffused weighting and the diffused area, play important roles in the class matrix optimization. An experiment is carried out using filters of different sizes as well as varying diffused weightings. The filters are co-optimized with the class matrix. Although the size of the class matrix can be varied, parallel processing efficiency declines as the size of the class matrix grows. To preserve the benefit of parallel processing, this study attempts to develop optimized class matrices of size $8 \times 8$ and $16 \times 16$ with their corresponding diffused weightings.

The devised class matrix is optimized in Mese’s approach. Second, Mese simply adopted the diffused weighting and diffused area are not carefully optimized in Mese’s approach. Although Mese’s class matrix provides excellent reconstructed halftones as will be shown in Section IV, we believe it can be further improved for the following reasons. First, the diffused weighting and diffused area are not carefully optimized in Mese’s approach. Second, Mese simply adopted the single tone 16 in the class matrix optimization, which causes difficulties in rendering image regions with other tones using the devised class matrix.

$$H(u,v) = aL^{b_{\exp}} \left( -\frac{1}{s(\phi)} \frac{\sqrt{u^2 + v^2}}{d\log(L + d)} \right)$$

where $s(\phi) = \left[ \frac{1 - k}{2} \right] \cos(4\phi) + \left( 1 + k \right) \frac{1}{2}$. (5)

Mese’s work adopted $a = 131.6$, $b = 0.318$, $c = 0.525$, $d = 3.91$, $L = 0.091$, $w = 0.7$, and $\phi = \arctan(u/v)$. The single tone 16 is employed in the optimization to develop the final class matrix.

Although Mese’s class matrix provides excellent reconstructed halftones as will be shown in Section IV, we believe it can be further improved for the following reasons. First, the diffused weighting and diffused area are not carefully optimized in Mese’s approach. Second, Mese simply adopted the single tone 16 in the class matrix optimization, which causes difficulties in rendering image regions with other tones using the devised class matrix.

$$PSNR = 10 \log_{10} \frac{P \times Q \times 255^2}{\sum_{i=1}^{P} \sum_{j=1}^{Q} \left( \sum_{m,n \in R} \sum_{x_i+m,j+n} u_{m,n}(x_{i+m,j+n} - b_{i+m,j+n}) \right)^2}$$

(7)
A. Performance Evaluation

Performance evaluation employed in this work is described as below. For an image of size \( P \times Q \), the quality of a halftone image is defined as (7), shown at the bottom of the previous page, where \( x_{i,j} \) denotes the original grayscale image; \( h_{i,j} \) denotes the corresponding halftone image; \( w_{m,n} \) denotes the LMS-trained coefficient at position \((m,n)\), and \( R \) denotes the support region of the LMS-trained filter. The size of \( R \) is fixed at \( 7 \times 7 \) when measuring the quality of halftone images. The LMS-trained filter \( w \) can be obtained from psychophysical experiments [25]. The other way to derive \( w \) is to use a training set of both pairs of grayscale images and good halftone result of them. Error diffusion, ordered dithering and direct binary
search (DBS) can be used to produce the set. The work adopts LMS to produce $w_{m,n}$ as follows:

$$\hat{x}_{i,j} = \sum_{m,n \in R} w_{m,n} b_{i+m,j+n} \quad (8)$$

$$\epsilon_{i,j} = (x_{i,j} - \hat{x}_{i,j})^2 \quad (9)$$

$$\frac{\partial \epsilon_{i,j}}{\partial w_{m,n}} = -2 \epsilon_{i,j} b_{i+m,j+n} \quad (10)$$

where $w_{i,j,\text{opt}}$ denotes the optimum LMS coefficient; $\epsilon_{i,j}$ denotes the MSE between $x_{i,j}$ and $\hat{x}_{i,j}$; and $\mu$ denotes the adjusting parameter used to control the convergent speed of the LMS optimum procedure, which is set to be $10^{-5}$ in this work. Some other quality evaluation methods can be found in [26] and [27].

B. Diffused Weighting and Class Matrix Co-Optimization

To conduct the diffused weighting and class matrix co-optimization, some constraints in diffused weighting must be met.

1) Those coefficients nearer to the center of the diffusion matrix have higher values.
2) Those coefficients with the same Euclidean distance to the center of the diffusion matrix have the same values.

3) The nearest vertical and horizontal coefficients are fixed as 1.

The first constraint is to accommodate human vision characteristic. The second and third constraints are to reduce the number of possible coefficient combinations in diffused weighting. For example, if the diffusion matrix is of size $3 \times 3$, only one value in the four corners needs to be optimized. Instead of individually optimizing diffused weighting and class matrix, the two key components are co-optimized. During the class matrix optimization, each member in the class matrix is successively swapped with one of the other 63 members (assuming the class matrix if of size $8 \times 8$) and applied to the eight testing images. Each swapping involves switching all potential diffused weightings. Each potential weighting is obtained by adjusting $10^{-5}$ to its previous value. The quality evaluation approach introduced in Section III-A is employed to evaluate the average PSNRs (before and after swapping and switching) of the corresponding dot-diffused halftone images. Only the combination that achieves the highest PSNR is selected, and the above procedures are repeated until swapping in class matrix and switching in diffused weighting no longer improve the PSNR. Comparatively, Mese’s method simply adopts the single tone 16 for class matrix training, making it difficult to render image regions with other tones. In contrast, this study adopts eight different natural images in its training procedure, allowing the optimized class matrix and diffused weighting to adapt to different tones in an image more adequately. The steps of the optimization procedure are detailed as below. The corresponding flow chart is illustrated in Fig. 4.

Step 1) Given an initial class matrix $C$ (Mese’s class matrix is employed).

Step 2) Four initial filters of sizes $3 \times 3$, $5 \times 5$, $7 \times 7$ and $9 \times 9$ are employed as diffused weighting with different diffused areas in the testing.

Step 3) Suppose the members within class matrix are ordered as a 1-D sequence. Successively swap each member $C(i)$ in the class matrix with one of the other 63 members $C(j)$ (given a class matrix is of size $8 \times 8$), where $i \neq j$.

Step 4) Generate potential diffused weightings by adjusting $10^{-5}$ in all its coefficient values. During the diffused weighting generation, the nearest vertical and horizontal coefficients are fixed as 1, and the coefficients with the same Euclidean distance to the center of the diffusion matrix are kept at the same value.

Step 5) Evaluate the average PSNR of the dot-diffused halftone images using the class matrix and diffused weightings obtained from Step 3 and 4. Let the LMS filter of size $7 \times 7$ be the HVS filter $w_{m,n}$, as indicated in (7).

Step 6) The swapped class matrix and the switched diffused weighting that lead to the highest reconstructed image quality, $\max(\text{PSNR}(\text{swapped } C, \text{ switched } H))$, is used as the new class matrix and diffused weighting. Otherwise, the swapped members are returned to the original position in the class matrix.

Step 7) Select another member $C(i)$ in the class matrix, and then performs Steps 4 to 6.

Step 8) If any swapping and switching do not improve the resulting quality of the reconstructed dot-diffused image, terminate the optimization procedure. Otherwise, repeat Steps 3–7.

Fig. 5 shows eight diffused weightings obtained from above procedure. The coefficient values are interpolated to fill each floating point locations. Since the center value is useless, it is fixed as zero throughout the optimization procedure. Table I shows the final convergent class matrices obtained with the optimization procedure above. The table does not include $8 \times 8$ and $16 \times 16$ class matrices with optimized diffused area $5 \times 5$, $7 \times 7$ and $9 \times 9$, as these do not yield results superior to the one obtained by filter of size $3 \times 3$. The reason that the diffused area of size $3 \times 3$ performs the best is that it violates the causality the least.

IV. EXPERIMENTAL RESULTS

Eight different testing images are used to test the performance of the proposed algorithm. Equation (7) is adopted to evaluate the PSNR, using the LMS-trained filter of size $7 \times 7$ shown in Fig. 3.

The best diffused weighting and its corresponding diffused area is first identified. Fig. 6(b)–(i) shows the dot-diffused images processed by the eight optimized class matrices. Among these, Fig. 6(b) has the maximum PSNR of 33.33 dB for the class matrix of size $8 \times 8$, and Fig. 6(f) has the maximum PSNR.
Fig. 11. Dot-diffused images obtained from continuous ramp map. (a) Original grayscale image. (b) Class matrix of size $8 \times 8$ using in proposed method and (c) Mese’s method [4]. (d) Class matrix of size $16 \times 16$ using in proposed method and (e) Mese’s method. (All printed at 200 dpi). (b) PSNR = 35.10 dB; (c) PSNR = 32.40 dB; (d) PSNR = 35.39 dB; (e) PSNR = 35.08 dB.

of 34.13 dB for class matrix of size $16 \times 16$. The best class matrices are both obtained by diffused area of size $3 \times 3$. Fig. 7 shows the exact diffused weightings, where the variable $x$ denotes the pixel currently being processed. Since the diffused
weighting is co-optimized with the class matrix, the optimal class matrix is obtained simultaneously with the optimal diffused weighting. The two optimized class matrices of size $8 \times 8$ and $16 \times 16$ associate to the two optimized diffused weighting in Fig. 7(a) and (b) are shown in Table I(a) and (b), respectively. Although we set constraints in the optimization by fixing the four vertical and horizontal elements as 1 and the four elements in the corners with the same floating value, the reconstructed image quality is still improved with this co-optimization strategy, as shown in Fig. 6. To further reduce the deficiency of using floating point diffused weighting, we use weightings according to the power relationship shown in Fig. 7(c). Notably, the class matrices are still the ones in Table I(a), (b). The reconstructed dot-diffused results are surprising in that they are simply slightly inferior to the results from co-optimization as shown in Fig. 8 with diffused area of size $3 \times 3$. The reason that the image quality using power fashion filter degrades rapidly is that when the filter size increases, the differences of between the power fashion coefficients and the optimal floating point coefficients increase as well. The variables CM and DW denote the class matrix and diffused weighting, respectively. It is apparent that the image quality decreases as the diffused area increased. The reason can be explained by the fact that optimization does not guarantee global optimum, and when the search space increases, the probability of getting stuck to local optimums increases. Hence, the class matrices, as shown in Tables I(a), (b), which are co-optimized with the diffused weighting of size $3 \times 3$ are adopted for the proposed dot diffusion. In fact, a better result can be obtained by modifying Step 8 and adding an extra Step 9 in co-optimization procedure as below.

Step 8. If any swapping and switching do not improve the resulting quality of the reconstructed dot-diffused image, record the temporary local optimized diffused weighting and class matrix. Otherwise, repeat Steps 3–7.

Step 9. Randomly permute the convergent coefficients of class matrix obtained in Step 8, and repeat Steps 3–9 until a satisfactory result is obtained.

It took us about two months to finish one round (Steps 1–8) using the original co-optimization version. If the readers are interested in generating a better result, the above modified co-optimization version (Steps 1–9) is suggested.

Another observation is that the optimized diffused weighting matrices for $8 \times 8$ and $16 \times 16$ matrices are different. Since this work tries to propose a new dot diffusion by co-optimizing diffusion matrix and class matrix simultaneously, it is not surprising to obtain different diffusion matrix for class matrix of different sizes. However, as indicated above, the diffusion matrices and class matrices obtained in this work should not be global optimized results. It is difficult to provide a precise rationale for the experimental results, since the global optimized results may have identical diffusion matrices for $8 \times 8$ and $16 \times 16$ class matrices.

A series of experiments are conducted to compare Mese’s and the proposed dot diffusion. In Mese’s, the single tone 16 is utilized for optimization. In contrast, eight natural images are employed for co-optimization in this work. Fig. 9 shows four patterns with greyscales 16, 33, 81, and 116 for performance comparison. As expected, Mese’s method achieves better image quality with tone 16. However, the proposed method is superior to Mese’s method in tones 33, 81, and 116. Fig. 10 shows...
the results of testing all grayscales ranging from 0 to 255. The proposed method outperformed Mese’s method by a large margin. The average PSNR values of the proposed method and Mese’s method using class matrix of size $8 \times 8$ are 34.63 and 32.46 dB, respectively, and the average PSNR of the proposed method and Mese’s method using class matrix of size $16 \times 16$ are 35.58 and 34.71 dB, respectively. Another comparison is conducted with the ramp map, as shown in Fig. 11.
The results of this comparison is consistent with that of the other experiments: The PSNR values of the proposed method and Mese’s method are 35.1 and 32.4 dB, using the class matrix of size 8 × 8, and 35.39 and 35.08 dB, using the class matrix of size 16 × 16. Another natural image of higher resolution of size 512 × 512 is also shown to compare the performance of the proposed method and Mese’s method with class matrix of size 16 × 16. Fig. 12 shows the result, revealing that the proposed method produces better blue noise distribution than Mese’s method. Some of them can be appreciated from the enlarged parts.

Fig. 13 shows the halftone results obtained by various halftoning methods, namely error diffusion by Floyd [5], Jarvis [6], Stucki [7], Ostromoukhov [8], Shiuai [11] and Li [13]; dot diffusion by Knuth [3] and Mese [4]; ordered dithering [1] with Classical-4 clustered-dot dithering and Bayer-5 dispersed-dot dithering, and DBS [23]. Fig. 14 shows the comparisons of average image quality and processing efficiency of above halftone techniques. Fig. 14(a) clearly indicates that the proposed dot diffusion has close image quality to error diffusion and far better than ordered dithering. Although the proposed method has lower quality than some error diffusion methods and DBS, its better processing efficiency as a result of parallel processing makes it superior to error diffusion or iteration-based DBS. The experimental results are shown in Fig. 14(b), which is yielded by a computer with Windows XP Professional Edition SP2 operating system, Intel Core (TM) 2 CPU 2.13 GHz, RAM 1.98 GB using 100 test images of size 512 × 512. Among these, the average processing efficiency of dot diffusion is higher than error diffusion about 10^3 times and higher than DBS about 10^6 times.
The Tone-Dependent Error Diffusion (TDED) 13 produces halftones with quality approximate to that of DBS. Based on TDED, two other extended approaches, called Block Interlaced Pinwheel Error Diffusion (BIPED) 14] and Serial Block-Based Tone-Dependent Error Diffusion (SBB-TDED) 15], are proposed to improve the processing efficiency and reduce the on-chip memory requirement of error diffusion, respectively. SBB-TDED provides excellent image quality which approximates to DBS results. However, the SBB-TDED does not have the parallel processing advantage as that in dot diffusion. On the other hand, BIPED divides the image into inward blocks and outward blocks to achieve parallel processing advantage. However, the inward and outward scan paths are conducted successively. In other words, the outward block diffusions must be completed before the inward blocks are processed. Hence, it requires processing time twice that of dot diffusion. One example of the inward and outward spirals is shown in Fig. 15. The processing order of BIPED has to follow these two types of spirals. Hence, the processing order of BIPED must be specified, which is similar to the function of the class matrix in dot diffusion. Moreover, the BIPED requires storing 128 sets of diffused weightings and thresholds, whereas dot diffusion simply requires one set of diffused weighting and threshold. In addition, the BIPED needs to store a 128 x 128 DBS pattern to deal with the checkerboard-like patterns due to limit-cycle behavior at the mid-tone and quartertone levels. Hence, the memory consumption of the BIPED is much higher than that in dot diffusion. Notably, the same memory consumption is also required in SBB-TDED. Based on the discussions above, the proposed dot diffusion still has the advantage of better parallel processing property and lower memory consumption. Although the proposed dot diffusion has these advantages, we would like to highlight that the BIPED and SBB-TDED provide excellent image quality. Suppose the application is quality oriented, the BIPED and SBB-TDED approaches are still strongly recommended.

V. CONCLUSION

This study proposes an improved dot diffusion that preserves parallel processing capability, while reducing the disparity in image quality with error diffusion. To bridge this disparity, a new co-optimized diffused weighting and class matrix is employed. Four different diffused areas are tested, and the experimental results show that the area of size 3 x 3 yields the best results. During optimization, natural images are used to provide more objective results for different tones. Results also indicate that the proposed method has better quality than Mese’s method in most tones, since tone 16 is the only tone level utilized in the training set by Mese. The proposed method is also compared with various halftoning methods, including direct binary search (DBS), error diffusion, ordered dithering, and previous dot diffusion. The comparisons show that the proposed dot diffusion achieved quality close to some methods of error diffusion. Moreover, since the proposed dot diffusion preserves the important parallel processing advantage, it provides higher executing efficiency than DBS or error diffusion. We, therefore, conclude that the proposed dot diffusion method can potentially contribute significantly to the practical printing industry and color quantization applications.

Nonetheless, the proposed approach still has two disadvantages.

1) Periodic patterns: Although the proposed approach improves the dot diffusion quality as compared to traditional approaches, some periodic patterns can still be perceived when a large area in the image has monotonic grayscale. This problem may be solved if more complex strategies are applied, such as devising tone dependent diffused weighting or involving DBS patterns in some grayscales as that used in TDED. These two ideas are left for future works.

2) Hardware implementation of floating point diffused weighting: This part has been significantly eased, since during the optimization procedure, the vertical and horizontal weightings are maintained as 1, and the four diagonal weightings have the same value. Moreover, we observed that if the floating diffused weightings are replaced with the power coefficients (2 for vertical and horizontal, and 1 for diagonal), while maintaining the use of the class matrix devised from the floating point diffused weighting, the resulting dot-diffused image still attained excellent image quality.

REFERENCES


Jing-Ming Guo (M’06) was born in Kaohsiung, Taiwan, R.O.C., on November 19, 1972. He received the B.S.E.E. and M.S.E.E. degrees from the National Central University, Taoyuan, Taiwan, in 1995 and 1997, respectively, and the Ph.D. degree from the Institute of Communication Engineering, National Taiwan University, Taipei, Taiwan, in 2004. From 1998 to 1999, he was an Information Technician Officer with the Chinese Army. From 2003 to 2004, he was granted the National Science Council scholarship for advanced research from the Department of Electrical and Computer Engineering, University of California, Santa Barbara. He is currently an Associate Professor with the Department of Electrical Engineering, National Taiwan University of Science and Technology, Taipei. His research interests include multimedia signal processing, multimedia security, digital halftoning, and digital watermarking. Dr. Guo is a member of the IEEE Signal Processing Society. He received the Research Excellence Award in 2008, the Acer Dragon Thesis Award in 2005, the Outstanding Paper Awards from IPPR, Computer Vision and Graphic Image Processing in 2005 and 2006, and the Outstanding Faculty Award in 2002 and 2003.

Yun-Fu Liu was born in Hualien, Taiwan, R.O.C., in 1984. He received the B.S.E.E. degree from Jin Wen University of Science and Technology, Taipei, Taiwan, in 2004, and the M.S.E.E. degree from Chang Gung University, Taoyuan, Taiwan, in 2009. He is currently pursuing the Ph.D. degree in Department of Electrical Engineering, National Taiwan University of Science and Technology, Taipei. His research interests include intelligent transportation system, digital halftoning, and digital watermarking.